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Title: Do Rural Incentives Payments Affect Entries and Exits of General Practitioners?

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Do Rural Incentives Payments Affect Entries and Exits of General Practitioners?

Abstract

Many countries use financial incentive programs to attract physicians to work in rural areas. This paper examines the effectiveness of a policy reform in Australia that made some locations newly eligible for financial incentives and increased incentives for locations already eligible. The analysis uses panel data (2008 to 2014) on all Australian general practitioners (GPs) aggregated to small areas. We use a difference-in-differences approach to examine if the policy change affected GP entry or exit to the 755 newly eligible locations and the 787 always eligible locations relative to 2,249 locations which were never eligible. The policy change increased the entry of newly-qualified GPs to newly eligible locations but had no effect on the entry and exit of other GPs. Our results suggest that location incentives should be targeted at newly qualified GPs.

Keywords: Australia; GP rural incentives; GP geographic distribution; GP location choice; entries and exits.

Word Count: 7,558

1. Introduction

Significant policy and research effort is directed at understanding the effect of financial incentives on physicians' provision of healthcare (Eccles et al., 2010; Scott et al., 2011). A less studied area is the use of financial incentives to address geographical inequities in access to healthcare by influencing physician's location decisions (Simoens and Hurst, 2005).

Most countries have problems in ensuring equitable access to general practitioner (GP) services in rural areas. The difficulty of attracting and retaining GPs to work in small isolated rural communities is well documented. Although financial incentive programs are widely used to address this problem, there is little evidence about their efficacy. Systematic reviews of a range of interventions to improve physician distribution report few high quality studies of financial incentives. Dolea et al. (2010) found three studies of financial incentives with some positive effects, but these were based on surveys of physicians asking them whether incentives would influence their behaviour, or before-and-after studies with no control group. Wilson et al. (2009) found only two studies of direct financial incentives and concluded that there was little quantitative evidence to support their use. Grobler et al. (2009) reviewed 1,844 studies but found no studies satisfying the review's study design inclusion criteria. This review was updated in 2015 and found only one study meeting the inclusion criteria, but it did not examine financial incentives (Grobler et al., 2015). Buykx et al (2010) found little evidence demonstrating the effectiveness of any retention strategies based on financial incentives.

Due to the scarcity of revealed-preference evidence, researchers have also used stated-preference approaches to shed light on the potential effectiveness of financial incentive schemes (Hanson and Jack, 2010; Kolstad, 2011; Scott et al., 2013; Li et al., 2014; Holte et al., 2015). Many of these studies found substantial financial incentives would be required to induce GPs to change locations. For example, Scott et al. (2013) report that 65% of the Australian GPs in their sample would not move to a small town under any circumstances, and others would only move if they receive a 64% pay rise. Holte et al. (2015) estimate that a 20% pay rise could increase the number of GPs choosing a rural location by 12 percentage points in Norway. These studies suggest very large incentives that may not be feasible in practice are necessary to affect GP location choices, and that relatively small incentives may not have any impact. Evaluations of actual incentives programs are needed to validate these results.

This paper provides the first rigorous evaluation of the impact of financial incentives designed to influence the location choices of GPs. Our approach relies on a policy change in Australia in 2010, when the system used to classify remoteness was changed. Because of this exogenous change, some locations previously ineligible for rural incentive payments became newly-eligible post-2010. Exploiting this change in eligibility status, we conduct difference-in-differences analysis using data on the locations and mobility of the population of GPs in Australia over a six-year period, including two years before the policy change and four years after. We compare GP movements in and out of these newly eligible geographic locations (and movements in and out of always eligible locations) with movements in and out of locations that were never eligible for incentive payments before and after the classification change. This study is also the first to distinguish different types of entries and exits of GPs.

In Australia, GPs are paid by fee-for-service for consultations, and patients receive a fixed subsidy or rebate (around AUD$37 in 2017) from Medicare, the universal tax-financed national health insurance scheme. However, there are no restrictions on the fees GPs can charge patients and patients can face a co-payment if the fee is more than the rebate. GPs can also price discriminate so that fees may vary across patients. The practice of charging no co-payment is known as "bulk billing." An additional rebate or "bulk-billing incentive" is available to GPs who charge zero co-payment to certain groups of patients: children under 16 and low-income patients who hold concession cards. In recent years approximately 80 per cent of GP services have been bulk-billed (AIHW, 2016).

Most GPs are free to practise in any geographic location, but there are some exceptions: if the GP is qualified overseas, or is a graduate of a medical school in Australia but studied as an international student, or is otherwise bonded at medical school entry. GPs in these categories can only bill Medicare if they work in locations labelled 'District of Workforce Shortage' (DWS) for between five and ten years, depending on remoteness of the DWS location.

As there may be less demand for health care in rural areas with small populations, GP's fee-for-service revenue can be insufficient to maintain a financially viable practice. Consequently, there is a range of subsidies to support rural medical practices and maintain access to health care in rural areas. Financial incentives to bulk-bill children and low-income patients are higher in rural than metropolitan areas. Similarly, there is a loading of between 15 and 50 per cent for rural GP practices in the Practice Incentive Program (PIP) which provides incentives for treating patients with specific chronic diseases and for practice infrastructure (Department of Human Services, 2013).

In addition, there are specific financial incentives to encourage GPs to locate to, or stay in, rural areas. Australia first introduced a rural incentive program for GPs in 1994 (Holub, 1995) and this became the Rural Retention Program (RRP) in 1998. In July 2010, the General Practice Rural Incentives Program (GPRIP) was introduced to streamline and consolidate previous rural incentive programs, including the RRP. The aim of GPRIP is to use direct financial incentives to recruit and retain doctors in rural areas. There are two components to the program: (1) the GP retention component provides incentives for GPs to remain in rural areas and (2) the Rural Relocation Incentive Grant (RRIG) aims to increase the recruitment of doctors to rural areas. The first is an on-going incentive payment depending on several factors (see below), whereas the second component is a one-off payment.

Table 1 shows the size of the GPRIP incentive payments introduced in 2010 and which did not change in the period of this study. This on-going payment depends on: (i) the location, defined using the five-category Australian Geographic Standard Classification–Remoteness Area (AGSC-RA), under which RA1 designates major cities which are not eligible for incentive payments, (ii) the length of time the GP has practised in eligible locations, so that GPs who worked in these location for five years or more receive the largest payments of between $12,000 and $47,000, and (iii) volume of services provided – GPs must provide more than a specified minimum quantum of clinical services in these locations ($4,000 of billed items in each quarter). GPs become eligible for the payments after two or four ‘active’ quarters (depending on remoteness) in these locations, where ‘active’ means meeting the minimum volume requirement (iii). **Table 1** shows the maximum possible incentive payment made to GPs who bill Medicare for $80,000 or more for four active quarters. GPs whose workload is less will receive proportionately less (e.g. if a GPs bills \$40,000 they will receive half the payment). At the time GPRIP was introduced, around 11,000 doctors were eligible for these payments. Some specialists were also eligible under the scheme but this paper focuses on GPs (Mason, 2013). GPs in areas that were always eligible for incentives did not lose incentive payments under the new scheme, and would receive higher payments after five years. Further detail about the change in the scheme and the size of incentives is given in Appendix A. Though the first GPRIP component is mainly aimed at retaining GPs in incentivised locations, it can also influence GPs' decisions to move to or leave rural areas as the incentive payments will influence their future expected lifetime earnings in different types of location.

The second GPRIP component is focused on encouraging recruitment – RRIG provides relocation grants to doctors who move to a rural location. For example, the maximum payment of AUD\$120,000 one-off payment is paid to a GP who moved from a metropolitan location (RA1) to a very remote location (RA5). We examine the overall effect of both components although the fact that in 2011-12 only 33 doctors received RRIG payments (and RRIG was later discontinued in 2015) suggests that it is not as important as the retention component of GPRIP.

For this paper, the key change in July 2010 was the introduction of a different geographic classification scheme (ASGC-RA) which was used to determine the eligibility for GPRIP. Because of this change, all ASGC-RA2 areas, and some ASGC-RA3 areas that were ineligible for incentive payments under the previous classification scheme, became eligible for incentive payments. We refer to these areas as 'newly eligible locations.' In total around

750 out of some 3,800 locations became newly eligible in July 2010. In newly eligible locations, all doctors were treated as newly eligible and could therefore initially only claim the lowest amount of $2,500 (see **Table 1**), no matter how many years they had previously been in the location. All doctors in newly eligible RA2 locations would therefore have received an exogenous increase in earnings of up to $2,500 after the first year, increasing up to $12,000 after five years, subject to claiming rules. After five years, the cumulative additional earnings are $34,000 or an average of $6,800 per year. In 2010, the average annual earnings of a GP before tax (but after practice expenses) was about $180,000 (Cheng et al., 2012), suggesting that GPs on average would experience an increase in earnings of up to 1.4 per cent per year after the first year of the scheme, increasing to 6.6 per cent after five years, or an average earning increase of up to 3.8 per cent per year in the first five years. For those who stay in eligible locations the incentives increase their lifetime earnings. Note this is a relatively small incentive compared to that suggested by the stated preference literature discussed earlier.

2. Data and Methods

2.1 Data

We map the distribution of GPs and identify entries and exits, using the Medical Directory of Australia, compiled by the Australian Medical Publishing Company (AMPCo). The dataset is a census of all doctors in active practice on a single date in May each year. Information collected includes practice location, gender, age, qualification, and place of qualification. The data are retrospective administrative data of practising doctors in Australia and since all information is in the public domain, no ethics approval is required.

AMPCo data for seven years, 2008–2014, are used. The data allow the tracking of doctors over time since each doctor in the dataset has a unique time-consistent encrypted identifier. We restrict the sample to doctors who were GPs for at least one year during the period. GPs were aggregated into one of 3,800 locations (defined by a suburb-postcode combination) each year, and location is the unit of analysis.

We measure the *stock* of GPs in each area on each annual census day. We also break up the change in the stock into various types of entries and exits. The most numerous categories are GPs who move from one location to another, exiting from one location (recorded as *relocation exits*) to enter another location (recorded as *relocation entries*). There are also *new entries*: newly qualified GPs entering the workforce for the first time, *other entries*: entries other than relocation or new entries (e.g., GPs relocating from overseas, returning to work after a period of absence, etc.), and *other exits*: exits by GPs who do not move to another location, for reasons such as retirement, death, moving overseas, or leaving the profession. Appendix B contains a detailed description of the key variables and their construction and some further descriptive statistics.

2.2 Estimation

To evaluate the effect of GPRIP on entries and exits of GPs, we exploit the fact that due to the change in the remoteness classification in 2010, some locations previously ineligible for GPRIP became eligible post-2010. We employ a difference-in-differences regression approach and compare changes in the stock of GPs and entries and exits in two types of location − those that were *newly eligible* for GPRIP and locations that were *always eligible*, with a comparator group: locations *never eligible* for rural location incentives. GPs in newly eligible locations received between 1.4 to 6.6 per cent increases in earnings. GPs in always eligible locations would continue to get the payments they had received under the previous RRP scheme and would get the higher GPRIP payments if they stayed in an eligible location longer than five years.

The regression models we estimate are of the basic form

$$y_{jt} = \alpha_0 + \delta_t + \delta G_t + \gamma_1 N_{jt} + \gamma_2 A_{jt} + \theta_1(N_{jt} \times G_t) + \theta_2(A_{jt} \times G_t) + \beta_x X_{jt} + \varepsilon_{jt} \qquad (1)$$

where j and t denote location and year. The dependent variable y is one of six dependent variables: *stock* of GPs (in logarithm), *relocation entries*, *relocation exits*, *new entries*, *other entries*, and *other exits*; year effects are denoted by δ_t and X_{jt} are characteristics of GPs and the population in the location. We use the logarithm of the stock of GPs to account for the skewness of the distribution of GPs: the distribution has a mean of 7.6 GPs per location and median of 4 GPs, and ranging from the minimum of 1 GP to the maximum 112 GPs.

Two estimation methods are employed: ordinary least squares (OLS) and fixed effects estimation. OLS is robust to assumptions about the distribution of the error terms, unlike, for example, count data models. Fixed effects estimation is employed to account for unobserved time invariant location characteristics that may affect the stock and entries and exits of GPs.

In OLS specifications we assume the error ε_{jt} is i.i.d. With fixed effects regressions, we assume the error term in eq. (1) can be written as: $\varepsilon_{jt} = \alpha_j + e_{jt}$ where α_j denotes the location fixed effects and e_{jt} is the i.i.d. error term. With the fixed effects specification, all time-invariant covariates including the GPRIP eligibility status are dropped from eq. (1).

The key explanatory variables are the dummy variable G_t indicating whether the period is before or after the introduction of GPRIP in 2010 and the dummy variables indicating GPRIP eligibility status: A_{jt} always eligible, N_{jt} newly eligible, with never eligible as the omitted reference category. The parameters θ_1 and θ_2 capture the difference-in-difference estimates of GPRIP in respectively newly eligible and always eligible locations. These difference-in-difference estimates are relative to the omitted group – locations never eligible for financial incentives either under RRP or under GPRIP.

The baseline never eligible group of locations are not a comparator group in the usual sense of not being affected by the treatment, i.e., the change in incentive payments based on location. In principle, GP location decisions are based on *comparisons* of income and other factors in all types of location: relative, as well as absolute income, will affect their choices. Thus a policy change that increases financial rewards in some locations can potentially affect the supply of GPs in other locations where the absolute level of rewards is unchanged. The magnitude of the 2010 changes in the level of location payments was greatest in newly eligible areas, smaller in always eligible areas, and zero in never eligible areas. This suggests that the newly eligible areas would gain GPs relative to the always eligible and even more so relative to the never eligible. Hence, if incentive payments have the intended effects, we expect that $\theta_1 > \theta_2 > 0$, since θ_1 and θ_2 capture the effect of the increased incentive payments for newly eligible and always eligible locations.

Locations in the never eligible comparator group may differ from those in the always and newly eligible groups in observed and unobserved ways. To account for observable differences, we include two types of small-area characteristics as covariates in the regression analysis. The first is a set of population variables: the population size, the proportion who are female, and the proportion aged over-65. The data are obtained from the 2011 Census and hence are time invariant for this study. We also take account of socio-economic standing of areas by using the Socio-Economic Index for Areas (SEIFA index) constructed by the Australian Bureau of Statistics. Higher SEIFA values indicate greater relative advantage. In the fixed effects estimation, we also account for unobserved differences between locations and all time invariant area characteristics are absorbed into the location fixed effects.

Second, we include three variables derived from AMPCo data and which characterise the stock of GPs in each location: (i) the proportion of female GPs, (ii) the proportion of GPs over 65, and (iii) the proportion of GPs who obtained their medical qualifications overseas, i.e., foreign trained doctors (FTDs). We enter them in the regression models with a one-year lag due to the concern about potential reverse causality.

A potentially complicating factor for this study is the entry and exit of GPs who are international medical graduates (IMGs), most of whom are subject to the requirement to work in DWS for a stipulated period (between five and ten years depending on the practice location rurality). Note that IMGs are also eligible for incentive payments if they practice in GPRIP-eligible locations. Although DWS and GPRIP eligible locations sometimes overlap, they do not always do. DWS areas are revised more frequently than GPRIP eligibility. IMGs therefore face two different sets of policy influences when choosing a location: fulfilling

DWS restrictions and qualifying for incentive payments under GPRIP. Although IMGs must locate in a DWS area, incentive payments can be a factor influencing their choice within different DWS locations with different GPRIP eligibility status. To allow for DWS, we include a time-varying dummy variable in X_{jt} indicating whether a location was ever designated as a DWS in any given year. The variable is constructed from the DWS location data provided by the Department of Health and Ageing. We also estimate an alternative specification which excludes all locations ever designated as DWS during the sample period. The results, reported in Appendix C, are broadly similar.

3. Results

We identified a total of 3,791 locations (e.g. suburbs, communities, towns) in the data. The change in remoteness classification introduced in 2010 resulted in 755 locations previously ineligible becoming eligible for GPRIP after July 2010. Under both the old and new classifications, 2,249 locations, mostly in metropolitan areas, have never been eligible for any incentive payments, while 787 locations in rural areas have always been eligible. **Figure 1** shows the map of these locations by GPRIP eligibility status. It can be seen that newly eligible locations (denoted as triangles) are generally located in rural-fringe areas bordering the metropolitan locations (denoted as circles) which were never eligible for any incentive payments.

Table 2 presents some summary statistics about the number (or stock) of GPs and different types of entries and exits for all locations (definitions are provided in Appendix B). In total there were slightly more than 21,000 GPs in May 2009 in all locations, the number increased by about three per cent per year and reached about 24,000 GPs in May 2014.

The change in the stock of GPs in each location is made up of different types of entries and exits. The number of existing GPs who move from one location (i.e., *relocation exits*) to another (*relocation entries*) ranged from 1,500 to 2,300 annually during the study period. Note that by construction total *relocation entries* must equal total *relocation exits* when aggregated over all locations. In addition, *new entries* – GPs joining the workforce after completing their training – varied from 400 to 900 each year. *Other entries*, including GPs moving from overseas and returning after a period of absence, ranged from 500 to 1,200. *Other exits*, which include retirement and GPs leaving the workforce, ranged from 500 to 1,000 each year. *Net entry*, defined as the difference between all entries and all exits, ranged from 326 in 2013/14 to 1,187 in 2012/13.

To examine the change in entries and exits before and after 2010, we compute the annual average number of entries and exits of different types each year for all locations by eligibility status. The results are shown in **Figure 2**. The stock of GPs, other types of entries and exits exhibit similar trends across never eligible, newly eligible and always eligible locations. The consistent patterns across locations of different eligibility status suggest there is little anticipation or delayed effects of the policy change. For *new entries*, there is a sharp increase in 2010/11 across all locations but is highest for newly eligible locations. *New entries* then declined sharply for all locations in 2011/12 then rose again, but more strongly for newly eligible locations after 2012/13.

A key identifying assumption for the difference-in-differences estimates is the constant pre-treatment trend assumption, i.e., there should be no difference in trends between the treatment and comparator groups during the pre-policy change years. Visual inspections of **Figure 2** suggest no obvious diverging trends during the pre-policy change years. This is supported by formal tests of parameter estimates from models with year dummy variables interacting with the GPRIP dummy variable. Estimates from both OLS and fixed effects regressions do not reject the constant pre-treatment trend assumption; detailed test results are shown in Appendix C.

3.1 Stock of GPs in each location

To assess the overall effect of GPRIP, we estimate regression models using the stock of GPs in each location as the dependent variable. The key explanatory variables are eligibility status and its interaction with post-2010 dummy to capture the effect of GPRIP. The results are presented in Table 3 where four sets of regression results are shown. The first two are results from OLS regressions, the third is from fixed effects estimation while the last set is obtained from an OLS regression where the dependent variable is the first-difference i.e. the net entry in each location. The fixed effects estimation accounts for unobserved time invariant location characteristics, whereas the first-difference regression attempts to control for first-order serial correlation, a concern when using the stock of GPs in each location as the dependent variable since the stock is expected to show strong persistence over time.

The first OLS regression includes area-level population characteristics taken from the 2011 census. The second OLS regression includes as additional covariates area-level characteristics of GPs in each location. The fixed effects and first-difference regressions only include area-level characteristics of GPs since area-level population characteristics are time-invariant.

Table 3 shows that, compared to never eligible locations, newly eligible and always eligible locations had fewer GPs and the level appeared to be falling post 2010 although the coefficients are not statistically significant. Overall the results suggest that GPRIP did not have the intended effect of increasing the stock of GPs in newly eligible or always eligible locations, although there is also no evidence to suggest that the stock was falling in these locations post 2010.

The OLS regressions also show that locational characteristics such as population size, proportion of old people, and relative socio-economic advantage have a strong influence on the number of GPs in the location. More affluent areas have more GPs. Locations with proportionately more female GPs have more GPs, but the proportion of older GPs did not appear to have a consistent effect — it had a negative effect under OLS estimation, positive effect under first difference estimation and almost no effect under fixed effects estimation. The coefficients on DWS were consistently negative, likely reflecting that these areas are unattractive to GPs and hence why they were designated as DWS.

3.2 Entries and exits

Although GPRIP has no overall impact on the stock of GPs in eligible locations, there may still be differential impacts on different types of entries and exits. We next examine the components of the change in the stock of GPs in each location.

Two sets of regression models are estimated: OLS and fixed effects models for five dependent variables: *relocation entries*, *relocation exits*, *new entries*, *other entries* and *other exits*. The OLS results, reported in **Table 4**, show that compared to never eligible locations, newly eligible locations experienced a significant increase in *new entries* following the policy change in 2010 while always eligible locations appeared to experience an increase in both *relocation entries* and *relocation exits* post 2010. The magnitude of the increase in entries and exits is about equal and offsetting, resulting in no change in the number of GPs in these locations, as shown in **Table 3**. Overall the results suggest that GPRIP has positive effects on *new entries* in newly eligible locations, and on *relocation entries* and *relocation exits* in always eligible locations, but negative effects on *other entries* in both newly eligible and always eligible locations. The influence of small-area level population characteristics and characteristics of the stock of GPs is broadly consistent with the results in **Table 3**.

The fixed effects regressions reported in **Table 5** control for unobserved time-invariant locational characteristics. The results corroborate the OLS findings in **Table 4** – compared to never eligible locations, newly eligible locations attracted more *new entries* post 2010, and always eligible locations experienced an increase in both *relocation entries* and *relocation exits*, in approximately equal magnitude, but *other entries* were lower in newly eligible locations.

The difference-in-differences estimates for *new entries* in newly eligible locations are statistically significant at 1% under both OLS and fixed effects estimation with values of 0.068 and 0.080 respectively, which represent about half of the mean number of *new entries* of 0.15 per location during the study period. The estimates for always eligible locations for *relocation entries* and relocation exits from the OLS model are 0.062 and 0.066 and are slightly larger at 0.078 and 0.079 from the fixed effects models. The negative effects on *other entries* for newly eligible locations were respectively -0.08 and -0.071 under OLS and the fixed effects estimation, but these were less precisely estimated.

For newly eligible locations, GPRIP appeared to have no statistically significant effects on relocation entries and relocation exits, while for always eligible locations the policy change did not have any effects on new entries. In addition, for both newly eligible and always eligible locations, the policy change did not appear to affect other exits.

The coefficients on the covariates reported in **Tables 4** and **5** are plausible. Estimates on small-area population characteristics reported in **Table 4** show that population size and the SEIFA index have had strong and positive effects on entries and exits. The proportion of population aged above 65 years, had a negative effect on entries and exits but this was not statistically significant except in the case of *relocation exits*.

The DWS dummy variable has had consistently negative associations with entries and exits, although the effects were no longer statistically significant once the location fixed effects were included in **Table 5**. OLS and fixed estimates of the effects of characteristics of GPs in differ and in some cases the signs are reversed. It is possible that with fixed effects estimation, some unobserved time-invariant characteristics of locations that attract more female, or older GPs, or more FTDs, get absorbed into the fixed effects, thereby resulting in different estimates from those obtained via OLS.

3.3 Robustness checks

We undertook a number of robustness checks whose details are included in Appendix C. A formal test for parallel trends in the three types of location in the pre-policy change period did not reject the assumption (Appendix Table C1). However, the statistical tests are restricted by the availability of only two years of data for the pre-policy change period. Aggregate, national-level data appear to show a slight divergent trend in the stock of GPs between major cities and remote areas during the pre-treatment period though we do not believe it was serious enough to invalidate our model results; see Appendix C for further details.

Given that there were small numbers of entries and exits in some locations we also estimated negative binomial count data models. Results were qualitatively and quantitatively similar to the OLS estimates (Appendix C, Tables C2 and C3) but for *relocation entries*, *relocation exits*, and *other entries*, the estimated effects of the reform in always eligible locations were no longer statistically significant.

Although regression models can account for differences in covariates between the three types of areas, results can still be biased if the differences are large (Heckman et al., 1997). We therefore applied coarsened exact matching (Blackwell et al., 2009; Iacus et al., 2012) to the sample so that the estimation is restricted to more observationally similar treatment and comparison groups. The positive result on *new entries* into newly eligible locations remain robust and is slightly larger in magnitude, while the results on *relocation entries* into and *relocation exits* from always eligible locations are no longer statistically significant, perhaps because of the reduction in sample size (Appendix C, Tables C3, C4, C5).

Ideally in enumerating entries and exits we should exclude IMGs who are restricted in their location choice to DWS areas during their initial years of practice in Australia. Though these doctors are eligible for rural incentive payments, their decision to enter and stay in GPRIP eligible locations are less likely to be affected by the financial incentive than Australian doctors. However, the AMPCo data cannot reliably identify GPs who are required to practice in DWS. In the main models we control for this by including a DWS dummy as a covariate. In Appendix C, Tables C6 and C7 we adopt the alternative of dropping locations which are DWS.

After removing DWS locations from the estimation sample, the effect on *new entries* into newly eligible locations remain positive and statistically significant at 5% level, although smaller in magnitude. The effect of the policy change is also stronger for *relocation entries* but weaker for *other entries* and *relocation exits*.

Lastly, we attempt to smooth out year-to-year fluctuations in GP numbers, which may be due to lags in recording movements between locations, by taking the mean values of the GP stock, entries and exits pre- and post-policy change and use these mean values in the difference-in-differences regressions. The results (Appendix C, Tables C8, C9) are broadly similar to our previous results where we enumerate movements for the six years individually.

Overall, our main finding on the positive effect of financial incentives on *new GPs* remains robust to all variations considered in Appendix C. This is not the case for the effects of always eligible locations post reform on *relocation entries*, *relocation exits*, and *other entries*. For these locations, the estimated effects, become statistically non-significant under negative binomial and matched sample estimation. As noted before, the incentive effects of the reform on always eligible locations are likely to be small and variable, and as such could be sensitive to changes to the method and sample of estimation.

A key assumption required for the validity of our difference-in-differences analysis is that there were no unobserved confounding events that might affect GP location choices. We scanned for such potential confounding changes using the list of key general practice policies and initiatives compiled by Walters et al. (2017). We could not identify any policy events occurring in or around 2010 which might have affected location choices.

4. Discussion

We have examined the effectiveness of financial incentives in attracting and retaining GPs in rural locations in Australia. We applied difference-in-differences methodology by exploiting a change in the eligibility criteria in July 2010 which resulted in 755 locations previously not eligible for GP incentive payments becoming eligible. We expect that, if financial incentives were to positively affect the recruitment and retention of GPs, we should observe positive effects in these newly eligible locations.

Compared with never eligible locations in metropolitan areas, the extension of incentives to newly eligible areas attracted more newly qualified GPs. However, due to a negative effect on other entries and the lack of an effect on relocations by existing GPs, we find no evidence that the rural incentive program changed the overall stock of GPs in rural locations relative to metropolitan areas. On a more positive note, there is also no evidence that the overall stock of GPs fell in these areas. GPRIP is primarily intended to be a retention program, but our results show that it appeared to attract newly qualified GPs (recruitment) to these newly incentivized areas rather than impact on retention. We found no robust effect on existing GPs in always eligible locations. These areas did experience a change in incentives due to the policy change, but the change in incentives was small and delayed for GPs already in these locations.

The size of the effect for *new entries* is relatively substantial: a rise of between 0.068 and 0.080 relative to an overall mean number of new GP entries of 0.15 per location. The policy can be said to have increased *new entries* in newly eligible locations by around 50%. However, the number of new entries is relatively small in comparison to *relocation entries* (total *new entries* in the sample 1,700, total *relocation entries* 6,300). Hence there was no significant effect on the stock of GPs in incentivized locations.

Newly eligible areas tended to be more densely populated regional areas (RA2 and some RA3 locations), rather than the most remote areas which were always eligible for incentives. The effects of the scheme on always-eligible rural areas appeared negligible, possibly because the size of the incentives would be considered small relative to the much less attractive attributes of small population rural and remote areas. Another possible explanation for a lack of evidence of an overall long-term effect of incentives on location may be that our study covers a fairly short time period. It may take time for the information about new incentives to become known to existing GPs, and for them invest time and effort in choosing new locations.

Our results significantly extend the literature which has been characterized by a lack of high quality evidence (Grobler et al., 2015) or which has relied on surveys of GPs intentions rather than actual behavior (Dolea et al., 2010). Our results are comparable to the stated-preference literature that only examines existing GPs (i.e. not new GPs) and which tends to suggest that very large incentives are required to influence relocation decisions (Scott et al., 2013; Holte et al., 2015). Our results are consistent with the existence of fixed costs of relocation and unobserved attributes of the status-quo location experienced by existing GPs.

Mobility rates of currently practicing GPs are generally low, but increase with rurality (McGrail and Humphreys, 2015). Evidence from the U.S. suggests that a majority of GP movement occurs when they are early-career (young) and having been in their previous location only up to three years (McGrail et al., 2017). Outside these periods most GPs are satisfied and stable. Relocating practice usually has non-trivial consequences, especially in rural areas, involving either the GP enduring a longer commute, or they may have to move their household, with implications for family members, chief among them partners' occupation and children's schooling. Secondly the GP's current practice may have substantial unobservable attributes which the GP values. For example, they may have a friendly working atmosphere, a nice office, and a high degree of autonomy in their work schedule. Previous research shows most GPs are highly satisfied irrespective of their practice location (McGrail et al., 2010). These unobservable attributes are more likely to be important the longer a GP has worked in one practice and GPs cannot be sure if a potential new practice will offer the same benefits. Perhaps for these reasons most stated preference studies find that large financial incentives are required for existing GPs to change their practice locations. In comparison, newly-qualified GPs who are yet to 'settle' both professionally and possibly non-professionally are likely to be younger, have less family commitments, and not to own a practice. Thus the costs of moving and unobserved attributes attached to a location are likely to be less important in their location decisions. The policy implications of our results are that location decisions by newly qualified GPs can be influenced by financial incentives. Instead of providing financial incentives to all GPs, it will be more cost effective for policies to specifically target newly qualified GPs.

Appendices A, B, C. Supplementary Material

[Insert Link to Online Supplementary Material File]

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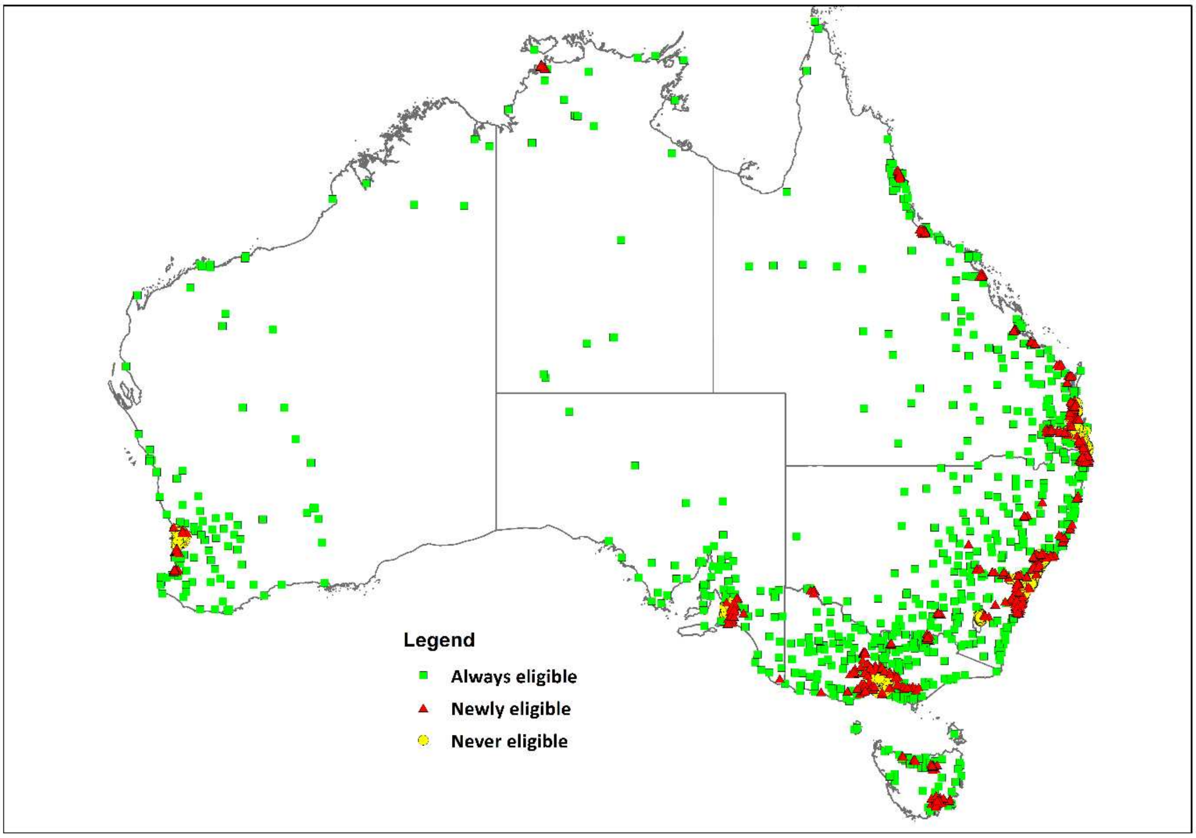
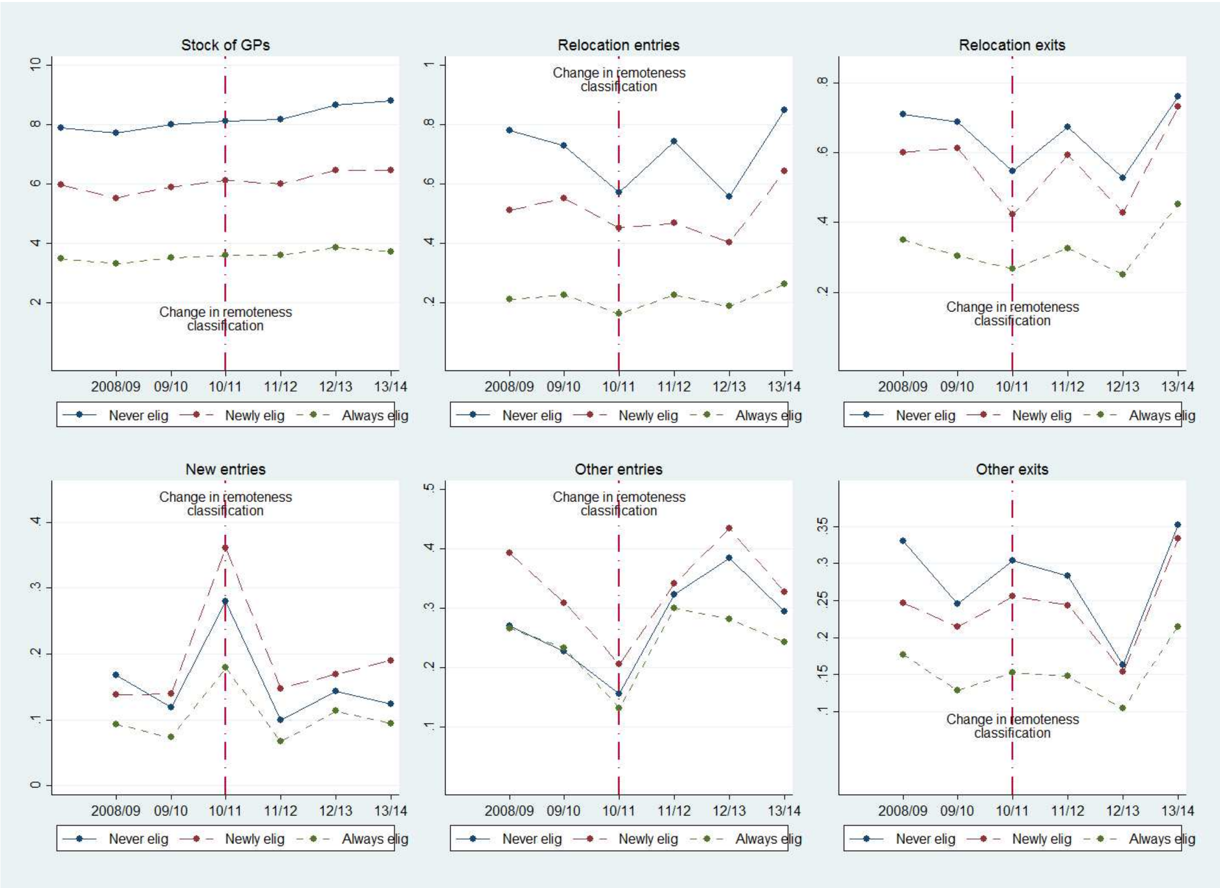
Figure 1: Map of locations by GPRIP eligibility status

Figure 2: Annual average number of GP stock, entries, and exits


Legend
Always eligible
Newly eligible
Never eligible



Note: Annual averages of stock, entries and exits are computed by taking the average across all locations by eligibility status for a given year.

Table 1. Incentive payments in the General Practice Rural Incentives Program.

	0.5 year	1 year	2 years	3-4 years	5+ years
RA2 (Inner Regional)	-	$2,500	$4,500	$7,500	$12,000
RA3 (Outer Regional)	$4,000	$6,000	$8,000	$13,000	$18,000
RA4 (Remote)	$5,500	$8,000	$13,000	$18,000	$27,000
RA5 (Very Remote)	$8,000	$13,000	$18,000	$27,000	$47,000

Table 2: GP Entry and exit counts, all locations

Year	Total No. GPs	Relocation entries/exits	New entries	Other Entries	Other Exits	Net Entry
2008/09	21,011	2,013	482	950	927	505
2009/10	21,456	1,901	362	773	690	445
2010/11	21,997	1,502	879	511	849	541
2011/12	22,571	1,940	334	1,059	819	574
2012/13	23,758	1,477	462	1,212	487	1,187
2013/14	24,084	2,270	426	950	1,050	326

Note: (1) Entries and exits were identified using data on a snapshot of all doctors in May of each year.

(2) Total No. of GPs in a given year, say 2008/09, refer to the stock figure in May 2009; while all entry and exit counts refer to the change between May 2008 and Apr 2009.

(3) By definition relocation entries = relocation exits when aggregated over all locations.

(4) Other entries include all entries other than relocation or new entries, eg, GPs moving from overseas, resuming practice after a period of absence, etc.

(5) Other exits include all exits other than relocation exits, eg, exits due to retirement, change of occupation, moving to overseas, etc.

(6) Net entry is the difference between all entries and all exits.

Table 3: Regressions of stock of GPs in each location on eligibility status

	Dep variable:	ln(number of GPs in location)		
Variable	OLS	OLS	FE	FD
Eligibility (Ref: Never eligible)				
Newly eligible	-0.161 **	-0.087 *	-	0.019
	(0.041)	(0.042)		(0.065)
Always eligible	-0.052	0.004	-	-0.098 ^
	(0.038)	(0.039)		(0.051)
Newly elig. × post-2010	-0.012	-0.052	0.023	-0.013
	(0.048)	(0.049)	(0.017)	(0.078)
Always elig. × post-2010	-0.033	-0.029	-0.018	-0.059
	(0.035)	(0.035)	(0.014)	(0.053)
ln(population)	0.277 **	0.295 **	-	
	(0.009)	(0.009)		
Prop. pop. older than 65 years	0.738 **	0.654 **	-	
	(0.138)	(0.141)		
SEIFA (per cent)	0.355 **	0.318 **	-	
	(0.042)	(0.044)		
District of Workforce Shortage (DWS)	-0.216 **	-0.213 **	-0.051 **	-0.002
	(0.025)	(0.026)	(0.017)	(0.038)
Prop. female GPs#		0.319 **	0.129 **	1.150 **
		(0.033)	(0.032)	(0.117)
Prop. GPs older than 65 years#		-0.240 **	0.042 ^	0.352 **
		(0.028)	(0.022)	(0.069)
Prop. foreign trained doctors#		-0.027	-0.008	0.273 *
		(0.025)	(0.031)	(0.124)
Constant	-1.459 **	-1.595 **	1.374 **	0.187 **
	(0.098)	(0.1010)	(0.018)	(0.039)
N	17661	16781	16781	16781
Adj. R2	0.118	0.140	0.034	0.014

Note: Figures in parentheses are robust standard errors.
OLS: Ordinary least squares estimation
FE: Fixed effects estimation
FD: First difference estimation
#Under FE the three covariates: Prop female GPs, GPs older than 60 and foreign trained, are lagged one period, under FD they are in first-differenced form.
Included as covariates but not shown in table are year dummies.
Significance levels: ^: 10% *: 5% **: 1%

Table 4: Ordinary least squares (OLS) estimation of types of entries and exits

	Dependent variable (number of GPs in location)				
Variable	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)					
Newly eligible	-0.195 **	0.034	0.029	0.147 **	0.005
	(0.052)	(0.057)	(0.019)	(0.036)	(0.851)
Always eligible	-0.194 **	-0.007	0.068 **	0.179 **	0.039
	(0.047)	(0.053)	(0.019)	(0.038)	(0.152)
Newly elig. × post-2010	0.051	-0.018	0.068 **	-0.080 **	0.024
	(0.039)	(0.047)	(0.020)	(0.030)	(0.025)
Always elig. × post-2010	0.062 *	0.066 *	0.013	-0.047 *	0.012
	(0.027)	(0.031)	(0.014)	(0.023)	(0.018)
ln(population)	0.157 **	0.174 **	0.062 **	0.120 **	0.063 **
	(0.014)	(0.016)	(0.006)	(0.011)	(0.008)
Prop. pop. older than 65 years	-0.230	-0.500 *	-0.138 ^	-0.479 **	-0.042
	(0.288)	(0.255)	(0.082)	(0.158)	(0.144)
SEIFA (per cent)	0.373 **	0.198 **	0.024	-0.010	0.186 **
	(0.083)	(0.076)	(0.026)	(0.042)	(0.039)
District of Workforce Shortage (DWS)	-0.058 *	-0.063 ^	-0.034 *	0.013	-0.037 *
	(0.027)	(0.036)	(0.015)	(0.026)	(0.019)
Prop. female GPs, lagged 1	0.076 *	0.159 **	0.041 **	0.014	0.083 **
	(0.032)	(0.033)	(0.011)	(0.019)	(0.016)
Prop. GPs older than 65 years, lagged 1	-0.063 *	-0.063 *	-0.038 **	-0.012	0.067 **
	(0.029)	(0.028)	(0.010)	(0.017)	(0.014)
Prop. foreign trained doctors, lagged 1	0.029	0.101 **	0.007	0.083 **	-0.058 **
	(0.031)	(0.030)	(0.010)	(0.019)	(0.015)
Constant	-0.943 **	-1.037 **	-0.431 **	-0.836 **	-0.388 **
	(0.167)	(0.176)	(0.060)	(0.111)	(0.091)
N	17587	17587	17587	17587	17587
Adj. R2	0.057	0.042	0.035	0.035	0.029

Note: Figures in parentheses are robust standard errors. Models also contain year dummies.
Significance levels: ^: 10% *: 5% **: 1%

Table 5: Fixed effects estimation of types of entries and exits

	Dependent variable (number of GPs in location)				
Variable	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)					
Newly elig. × post-2010	0.065	0.039	0.080 **	-0.071 *	0.038
	(0.040)	(0.051)	(0.022)	(0.032)	(0.026)
Always elig. × post-2010	0.078 **	0.079 *	0.014	-0.041 ^	0.027
	(0.028)	(0.032)	(0.015)	(0.024)	(0.019)
District of Workforce Shortage (DWS)	-0.018	-0.004	-0.025	-0.011	-0.014
	(0.038)	(0.059)	(0.029)	(0.042)	(0.030)
Prop. female GPs, lagged	-0.110 ^	0.225 **	-0.063 **	-0.078 *	0.081 **
	(0.060)	(0.056)	(0.021)	(0.034)	(0.030)
Prop. GPs older than 65 years, lagged	0.130 **	-0.031	-0.023	-0.109 **	0.179 **
	(0.046)	(0.041)	(0.016)	(0.026)	(0.022)
Prop. foreign trained doctors, lagged	-0.028	0.190 **	-0.042 *	-0.057	-0.104 **
	(0.069)	(0.064)	(0.021)	(0.037)	(0.030)
Constant	0.661 **	0.527 **	0.208 **	0.388 **	0.272 **
	(0.036)	(0.044)	(0.015)	(0.024)	(0.020)
N	17587	17587	17587	17587	17587
Adj. R2	0.013	0.013	0.024	0.018	0.018

Note: Figures in parentheses are robust standard errors. Included as covariates but not shown in table are year dummies. Significance levels: ^: 10% *: 5% **: 1%

Appendices A, B, C

Do Rural Incentives Payments Affect Entries and Exits of General Practitioners?

Appendix A: Incentive payments under GPRIP

The incentive scheme was modified in 2010 when GPRIP was introduced to streamline previous rural incentive programs. The size of payment depends on: (i) the location, (ii) the length of time practicing in eligible locations, and (iii) volume of services provided. At the time GPRIP was introduced, around 11,000 doctors were eligible for these payments. GPs in areas that were always eligible for incentives did not lose out under the new scheme. A 'grandfathering' arrangement was introduced for these GPs such that payments were calculated under GPRIP and the old scheme, known as the Rural Retention Program (RRP), and the GP was paid the higher amount until June 2013, after which they would be paid the GPRIP payment rates. The RRP payment rates are shown in **Table A1** according to the five types of eligible areas (A-E) defined using the GPARIA classification. For category A areas (least rural), GPs need to stay for 6 years before they qualified for a $5,000 payment. The qualifying period was only one year for the most rural area (category E).

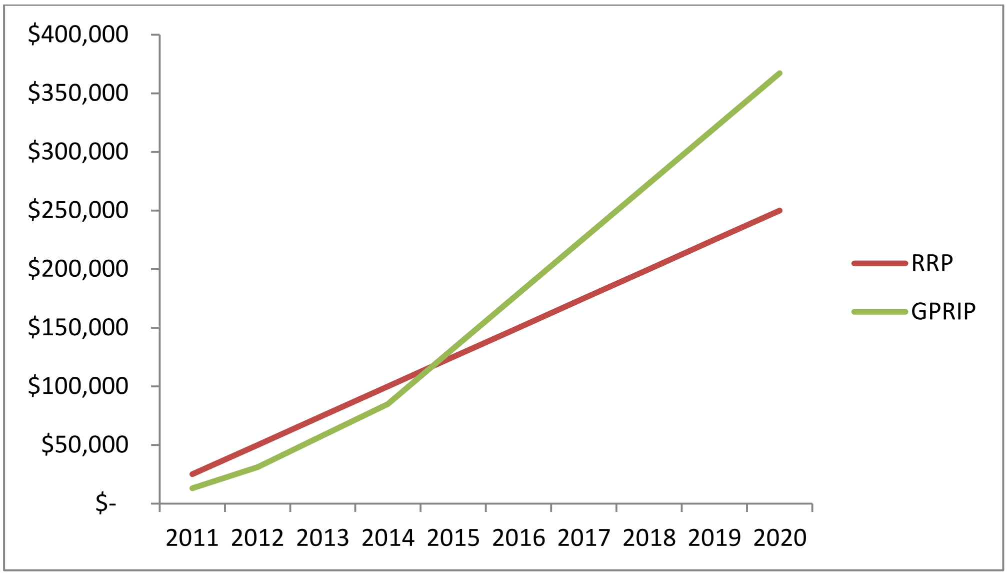
Table A1. Payments under the Rural Retention Program, pre July 2010 (GPs only)

Retention Payment Category	Qualifying Period	Maximum Annual Payment Rate
A (least rural)	6 years	$5,000
B	5 years	$10,000
C	3 years	$15,000
D	2 years	$20,000
E (most rural)	1 year	$25,000

Notes: GP Registrars were paid a lower amount.

Figure A1 compares the cumulative payments under each scheme assuming the GP had a one-year qualifying period. The figure shows the payments they would have received under RRP and the new payments under GPRIP if they were to stay in the same area (using Category E and ASGC RA-5 as an example). For these doctors the payment schedule became non-linear under GPRIP, such that for the first five years they would have been paid less (subject to the grandfathering arrangements), but after that the GPRIP became more generous than the old scheme. After 10 years the GP would have been paid $367,000 under GPRIP but only $250,000 under RRP, a difference of $11,700 per year, around 6.5 per cent of average GP earnings in 2010. Thus whether these changes increased the incentives for GPs to remain in locations that had always received the incentives depends on the rate of time preference of affected GPs. Those who stayed for less than five years would lose under the GPRIP compared to the RRP.

Figure A1. Comparison of payments under the RRP and GPRIP



Note: GPRIP figure was drawn for a hypothetical GP with a one-year qualifying period.

Appendix B: Data and variable construction

This appendix list the variables and covariates used in this study and describes their construction. Descriptive statistics of these variables are shown in **Table B1**.

Locations, entries and exits

The geographic unit on which GP entries and exits are tracked is a suburb-postcode location, an area smaller than the postcode unit; for example in a metropolitan area a postcode might contain several suburbs. This geographic measure, referred to as 'location' below, has the advantage that it can be matched into locations eligible for GPRIP and those not; unlike the postcode unit which could include locations eligible and not eligible for GPRIP in the same postcode. Entries and exits are identified by a GP being in one location in one year and a different location in the next. A GP moving from one location to another is an exit from the old location and an entry into the new location.

We define the following dependent variables.

- *Stock of GPs*: Total count of GPs at a given point in time (May of each year) in each location.
- *Relocation entries:* Entries into a location by existing GPs via a change in practice location during successive years. A relocation entry always has a corresponding relocation exit from another location.
- *New entries:* Entries from GPs in vocational training (GP Registrar or hospital doctor) who become a newly qualified GP and are choosing a practice to work in for their first job as a GP. Entries and exits of registrars (e.g., a registrar moving from one location to another) are not tracked in this study. A new entry is recorded if the doctor appeared as GP in year *t* for the first time while in year *t-1* was recorded as a GP registrar. To allow for delays in updating the administrative data, we also record as new entries doctors who appeared as GPs in year *t,* were missing from the data in year *t-1 and* in year *t-2* were recorded as GP registrars. Similarly for GPs missing from the data in year *t-1* and *t-2 and* were recorded as GP registrars in year *t-3*.

- *Relocation exits:* Exits by existing GPs leaving their existing practice location to practice in another location. A relocation exit always has a corresponding relocation entry into another location.
- *Other exits:* Exits other than relocation exits, including GPs leaving a location due to retirement, change of doctor type, moving overseas, leaving the profession, or leaving the labour force, whether temporarily or permanently. GPs appearing in year *t-1* in the data but recorded as missing in year *t* are counted as 'other exits' from their *t-1* locations.
- *Other entries:* Entries other than relocation or new entries. This category includes GPs moving from overseas (thus recorded in the data as GP for the first time), GPs returning to the workforce (e.g., from maternity leave, other profession, or retirement). GPs recorded as missing in the data in year *t-1* but appeared as GPs in year *t* are counted as 'other entries' into their year *t* locations.
- *Net entry*: The difference between total number of entries and exits.

Covariates

- *GPRIP eligibility status*: The eligibility of a location is determined by its remoteness classification. The remoteness classification scheme used was GPARIA prior to July 2010, the scheme was replaced by ASGC-RA after July 2010. Because of this change in classification, we can categorise locations into one of three eligibility status variables: (i) never eligible, denoting locations not eligible for incentives payments before and after July 2010, (ii) always eligible, denoting locations always eligible for incentives payments pre- and post-2010, (iii) newly eligible, denoting locations not eligible before July 2010 but becoming eligible after July 2010.
- *Population size:* Total population count at each location according to the 2011 Census. Note that this variable is time invariant because there is only one population census during the study period.
- *Proportion of population older than 65 years old:* Ratio of total count of population older than 65 years old to total population size. This variable is also taken from the 2011 Census.

- *SEIFA index:* SEIFA stands for Socio-Economic Indexes for Areas. Four different indexes were developed by the Australian Bureau of Statistics to rank areas in Australia according to relative socio-economic advantage and disadvantage. The specific index used in this paper is the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD). The index is constructed based on data from the 2011 Census.
- *District of workforce shortage (DWS)*: A DWS is a geographical area identified to have below average access to Medicare-subsidised health care services. The federal Department of Health is responsible for making DWS determinations. The list of DWS areas is published bi-annually. Although DWS and GPRIP eligible locations sometimes overlap, they do not always do. The DWS dummy takes on a value of 1 for a location in a given year if the location was ever designated as DWS during anytime of the year.
- *Proportion of female GPs*: Ratio of the total count of female GPs to total count of GPs in the location. The variable is constructed using registration information from AMPCo.
- *Proportion of GPs older than 65 years old*: Ratio of the total count of GPs older than 65 years to total count of GPs in the location. The variable is constructed using registration information from AMPCo.
- Proportion of foreign trained doctors: Ratio of the total count of foreign trained doctors (FTDs) to total count of GPs in the location. FTDs are identified from the institution name of their first medical degree as recorded in AMPCo data.

Table B1: Summary statistics of key variables

	Mean	std dev	Min	Max
Stock of GPs	7.96	10.25	1	112
Relocation entries	0.60	1.21	0	15
Relocation exits	0.62	1.20	0	25
New entries	0.17	0.50	0	9
Other exits	0.27	0.65	0	9
Net entries	0.20	1.67	-18	24
Eligibility status:				
Never eligible	0.63	0.48	0	1
Newly eligible	0.17	0.37	0	1
Always eligible	0.21	0.40	0	1
Population size (100,000)	14.65	15.84	0.001	39.086
Prop pop over 65 years old	0.15	0.06	0.000	0.447
SEIFA (percentile)	0.50	0.22	0.010	1.000
DWS	0.20	0.40	0	1
Prop female GPs	0.35	0.29	0	1
Prop GPs over 65 years old	0.28	0.30	0	1
Prop foreign trained GPs	0.35	0.33	0	1

Appendix C: Robustness Checks

1. Constant pre-treatment trend assumptions

A key identifying assumption for the difference-in-differences estimates is the constant pre-treatment trend assumption, i.e., the difference in trends between the treatment and comparator groups do not change over time during the pre-treatment years. Testing this assumption requires establishing a pre-treatment time trend, which requires sufficient data for the pre-treatment period. In this context the pre-treatment period consists of only two years: 2008/09 and 2009/10. We test the constant pre-treatment trend assumption by estimating models with annual time dummy interacting with the GPRIP dummy of the form:

$$y_{jt} = \alpha_0 + \delta_t + \delta G_t + \gamma_1 N_{jt} + \gamma_2 A_{jt} + \sum_{\tau=2008/09}^{2013/14} \theta_{1\tau}(N_{jt} \times D_\tau) + \theta_{2\tau}(A_{jt} \times D_\tau) + \beta X_{jt} + e_{jt} \quad (2)$$

where D_τ denotes the time dummy and the coefficients $\theta_{1\tau}$ and $\theta_{2\tau}$ capture the time trends for respectively the newly eligible and always eligible locations. A test of the constant pre-treatment trend assumption is a joint test of $\theta_{1\tau} = \theta_{2\tau} = 0$ for $\tau = 2009/10$ (note 2008/09 is the omitted reference year). The test results, summarized in **Table C1**, show that all regression models passed the test.

Table C1: Tests of constant pre-treatment trends

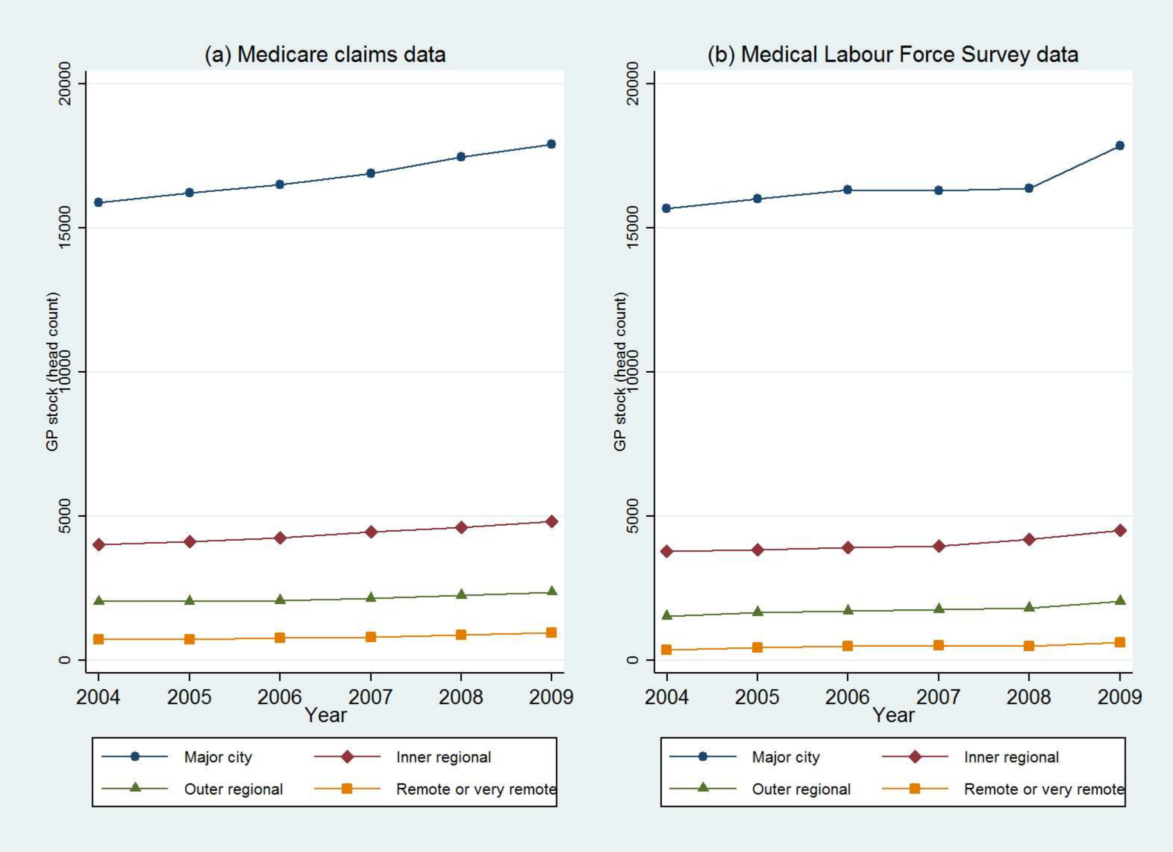
	Dependent variable					
	Stock of GPs	Relocation entries	Relocation exits	New entries	Other entries	Other exits
OLS regressions						
F-test	0.03	1.08	0.15	1.81	1.14	1.05
P-value	0.97	0.34	0.86	0.16	0.32	0.35
Fixed effects regressions						
F-test	1.00	1.13	0.21	1.93	1.28	1.62
P-value	0.37	0.32	0.81	0.15	0.28	0.20

Note: All models were estimated with the full set of covariates

It should be noted that we only had access to two years (2008/09 and 2009/10) of pre-policy change data. However, from other sources we are able to obtain aggregate, national-level GP stock statistics by remoteness area for the period 2004–09. Data from two different sources are shown in Figure C2: Australian Department of Health (DoH) and Australian Institute of Health and Welfare (AIHW). The DoH data were derived from data on Medicare service claims. The data include all GPs who have made a Medicare service claim during the indicated year; GPs who made no Medicare claims, e.g., GPs who work in hospitals or in administration roles, are not counted. The AIHW data relied on data collected from the annual Medical Labour Force Survey run by AIHW. The survey was discontinued in 2009.

The remoteness classification in the aggregate data does not match up exactly with the small-area data used in this study and so we cannot cleanly identify newly eligible areas in the aggregate data. For example, although most newly eligible locations are inner regional areas, some are classified as outer regional in Figure C2. Nonetheless, Figure C2 provides some useful information on the broad trend in the number of GPs across remoteness areas. In both data series GP stock has been broadly increasing across all areas. It is rising the fastest in major cities, followed by inner regional areas, with outer regional areas and remote or very remote areas showing little growth. Although the somewhat divergent trends between major cities and other remoteness areas are a concern, we do not believe that the divergence is so dramatic as to invalidate the difference-in-differences estimates.

Figure C2: National GP stock by remoteness area



Source: (a) General Practice Statistics, GP head count statistics, Department of Health

(b) Medical Labour Force Survey, AIHW

2. *Negative Binomial Models*

A concern with OLS or fixed effects estimation is the count nature of the data for different types of entries and exits. To allow for this feature of the data and also to allow for over dispersion, we estimate negative binomial models of entries and exits. The results are reported in **Table C2**.

Table C2: Negative Binomial estimation of types of entries and exits

Variable	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Always eligible)					
Newly eligible	-0.251 **	0.067	0.166	0.426 **	0.046
	(0.092)	(0.077)	(0.119)	(0.099)	(0.103)
Always eligible	-0.502 **	-0.047	0.310 *	0.560 **	0.132
	(0.117)	(0.096)	(0.146)	(0.120)	(0.117)
Newly elig. × post-2010	0.039	-0.041	0.340 **	-0.245 **	0.080
	(0.071)	(0.066)	(0.112)	(0.086)	(0.087)
Always elig. × post-2010	0.023	0.081	0.201	-0.135	0.045
	(0.087)	(0.068)	(0.129)	(0.089)	(0.092)
ln(population)	0.381 **	0.340 **	0.453 **	0.456 **	0.282 **
	(0.029)	(0.026)	(0.036)	(0.035)	(0.031)
Prop. pop. older than 65 years	-0.666	-0.870 *	-0.956 ^	-1.428 **	-0.400
	(0.552)	(0.438)	(0.570)	(0.546)	(0.574)
SEIFA (per cent)	0.668 **	0.338 **	0.176	0.000	0.671 **
	(0.135)	(0.118)	(0.163)	(0.147)	(0.144)
District of Workforce Shortage (DWS)	-0.232 **	-0.153 *	-0.244 **	0.039	-0.184 *
	(0.077)	(0.067)	(0.092)	(0.082)	(0.082)
Prop. female GPs, lagged	0.223 **	0.390 **	0.347 **	0.123	0.393 **
	(0.078)	(0.070)	(0.084)	(0.083)	(0.071)
Prop. GPs older than 65 years, lagged	-0.117	-0.128 *	-0.315 **	-0.087	0.324 **
	(0.074)	(0.064)	(0.080)	(0.077)	(0.064)
Prop. foreign trained doctors, lagged	0.003	0.209 **	0.023	0.313 **	-0.297 **
	(0.073)	(0.063)	(0.078)	(0.076)	(0.069)
Constant	-4.326 **	-3.829 **	-6.252 **	-5.655 **	-4.273 **
	(0.342)	(0.305)	(0.412)	(0.390)	(0.374)
ln(alpha)	0.504 **	0.279 **	0.686 **	0.849 **	0.329 **
	(0.042)	(0.041)	(0.069)	(0.048)	(0.070)
N	17587	17587	17587	17587	17587
Pseudo R2	0.044	0.028	0.041	0.030	0.028

Note: Figures in parentheses are robust standard errors.
Included as covariates but not shown in table are year dummies.
Significance levels: ^: 10% *: 5% **: 1%

With negative binomial estimation, the results on new entries and other entries into newly eligible locations are similar to those from the linear models — GPRIP has a positive and statistically significant impact on new entries, and a negative and statistically significant effect on other entries. However, the results on always eligible locations are different — the policy change has no statistically significant effect on relocation entries and other entries into and relocation exits from always eligible locations, although the signs are the same as with the linear models. Since the negative binomial is a nonlinear model, to obtain comparable difference-in-differences estimates, we compute the marginal effects of the interaction terms. The results are shown in **Table C3**. The marginal effect estimates on new entries and other entries into newly eligible location after the reform are statistically significant and very similar in magnitude to the respective OLS estimates reported in the paper (**Table 4).** An important difference from the OLS results is that relocation entries into and relocation exits from always eligible locations post reform, while still positive are no longer statistically significant in **Table C3**. Likewise, the estimate of other entries into always eligible locations post reform, while remains negative, is not statistically significant under negative binomial estimation.

Table C3: Negative binomial estimation, selected marginal effects

Variable	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Newly elig. × post-2010	0.023	-0.026	0.063 **	-0.068 **	0.023
	(0.043)	(0.040)	(0.024)	(0.022)	(0.026)
Always elig. × post-2010	0.013	0.053	0.036	-0.039	0.013
	(0.051)	(0.047)	(0.025)	(0.024)	(0.026)

Note: Figures in parentheses are delta-method standard errors.
Significance levels: ^: 10% *: 5% **: 1%

Note that the over dispersion parameter estimates, $\ln(\alpha)$, reported in **Table C2** are highly statistically significant in all models, suggesting that over dispersion is an important feature of the data.

3. Matching rural and urban locations

It can be argued that the sample contains locations that are vastly different in many ways—newly eligible locations tend to locate near the urban fringe, as can be seen in **Figure 1** of the text, whereas always eligible locations are mostly rural towns or centres away from urban cities. These locations are not only different in population size but also in terms of socio-economic characteristics such as income and unemployment. While regression analyses are able to account for some of these differences, concerns remain that the estimates could be affected by the incompatibility between the treatment and comparator groups.

To reduce the heterogeneity between the treatment and comparator groups, we match 1,531 locations in the two treatment groups (newly eligible and always eligible locations) with 2,245 locations in the comparator group (never eligible locations) using the coarsened exact matching (CEM) algorithm proposed by Iacus et al. (2011) and Iacus et al. (2012). Locations are matched using small-area population and socio-economic characteristics taken from the 2011 census: population size, median household income, proportion of population older than 65 years, proportion of population unemployed, and SEIFA percentile. These are characteristics of the postcode to which the location belongs, since the smallest area-level unit available from the census is the postcode. **Table C3** lists the matching variables and the coarsened categories we created for the purpose of matching.

Applying the coarsening in **Table C3** resulted in 528 strata, of which 134 strata found a match, i.e., strata consist of locations in the treatment and comparator groups. In total 1,124 locations (50%) and 826 locations (54%) in the comparator and treatment groups could be matched.

Using the matched sample, we re-estimate the OLS and fixed effects models. The results are shown in **Tables C4** and **C5**. Compared to the previous results, the models estimated on the smaller matched sample generally produce weaker statistical significance. However, the estimated effect of GPRIP on new entries are larger and statistically significant. The effects on relocation entries and relocation exits become smaller and are no longer statistically significant at five per cent level.

Table C3: Matching variables and coarsened categories

Variable	Coarsened categories
Population size	0–999 / 1,000–4,999 / 5,000–9,999 / 10,000–19,999 / 20,000–39,999 / 40,000–59,999 / 60,000+
Median household income ($)	0–999 / 1,000-1,399 / 1,400–1,799 / 1,800–2,199 / 2,200–2,599 / 2,600+
Prop above 65 years old (%)	0–4.99 / 5.00–9.99 / 10.00–14.99 / 15.00–19.99 / 20–24.99 / 25.00+
Prop unemployed (%)	0–2.99 / 3.00–4.99 / 5.00–6.99 / 7.00–8.99 / 9.00–10.99 / 11.00+
SEIFA (%)	0–19.99 / 20.00–39.99 / 40.00–59.99 / 60.00–79.99 / 80.00+

Thus the estimated positive effects of GPRIP on new entries into newly eligible locations are robust to removing incompatible locations from the sample, but results on relocation entries into and relocation exits from always eligible locations no longer hold. Similar results are obtained using fixed effects estimation, as shown in **Table C5**. GPRIP is found to have a large, positive and statistically significant effect on new entries into newly eligible locations—the estimated effect of 0.113 is larger than the previously reported fixed effects estimate where all observations are used in the estimation. In contrast to the previous results, the statistically significant results on relocation entries and other entries into, and relocation exits from always eligible locations no longer hold.

Table C4: OLS estimation of stock of GPs and types of entries and exits, matched sample

	Dependent variable					
Variable	Stock of GPs	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)						
Newly eligible	-0.077	-0.043	0.133	0.033	0.125 *	0.058
	(0.095)	(0.080)	(0.089)	(0.032)	(0.053)	(0.042)
Always eligible	0.077	-0.106	-0.047	0.032	0.151 **	0.079 ^
	(0.111)	(0.072)	(0.082)	(0.036)	(0.055)	(0.042)
Newly elig. × post-2010	-0.029	0.015	-0.083	0.092 **	-0.057	-0.044
	(0.040)	(0.067)	(0.073)	(0.034)	(0.045)	(0.039)
Always elig. × post-2010	-0.059	0.004	0.032	0.041	-0.088 ^	-0.037
	(0.042)	(0.060)	(0.066)	(0.034)	(0.047)	(0.038)
ln(population)	0.355 **	0.209 **	0.225 **	0.076 **	0.147 **	0.104 **
	(0.053)	(0.029)	(0.038)	(0.011)	(0.018)	(0.020)
Prop. pop. older than 65 years	1.268 ^	0.254	0.314	0.268	-0.201	0.209
	(0.740)	(0.368)	(0.484)	(0.269)	(0.276)	(0.207)
SEIFA (per cent)	-0.048	0.237	-0.088	-0.087 ^	-0.176 *	-0.010
	(0.245)	(0.149)	(0.167)	(0.049)	(0.084)	(0.091)
District of Workforce Shortage (DWS)	-0.231 **	-0.098 *	-0.115 *	-0.014	0.026	-0.024
	(0.078)	(0.043)	(0.054)	(0.025)	(0.042)	(0.028)
Prop. female GPs, lagged	0.223 ^	0.043	0.125 ^	0.048 *	-0.002	0.073 *
	(0.116)	(0.052)	(0.065)	(0.023)	(0.036)	(0.030)
Prop. GPs older than 65 years, lagged	-0.265 *	-0.082	-0.103 ^	-0.065 *	-0.028	0.051 ^
	(0.113)	(0.052)	(0.057)	(0.026)	(0.032)	(0.029)
Prop. foreign trained GPs, lagged	0.060	0.055	0.123 *	0.038	0.111 **	-0.017
	(0.100)	(0.048)	(0.061)	(0.025)	(0.035)	(0.026)
Constant	-2.010 **	-1.497 **	-1.504 **	-0.537 **	-1.002 **	-0.781 **
	(0.534)	(0.294)	(0.343)	(0.115)	(0.173)	(0.182)
N	8,101	8,291	8,291	8,291	8,291	8,291
Adj. R2	0.125	0.057	0.052	0.054	0.051	0.037

Note: Figures in parentheses are robust standard errors.
Stock of GPs is in natural logarithmic scale, all entries and exits are expressed in untransformed counts.
Included as covariates but not shown in table are year dummies.
Significance levels: ^: 10% *: 5% **: 1%

Table C5: Fixed effects estimation of stock of GPs and types of entries and exits, matched sample

	Dependent variable					
Variable	Stock of GPs	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)						
Newly elig. × post-2010	0.050 *	0.047	-0.035	0.113 **	-0.028	-0.032
	(0.025)	(0.066)	(0.076)	(0.036)	(0.046)	(0.040)
Always elig. × post-2010	-0.018	0.010	0.050	0.053	-0.069	-0.028
	(0.023)	(0.062)	(0.066)	(0.037)	(0.048)	(0.038)
District of Workforce Shortage (DWS)	-0.062 *	0.049	-0.087	-0.006	0.001	-0.020
	(0.025)	(0.063)	(0.079)	(0.049)	(0.075)	(0.045)
Prop. female GPs, lagged	0.142 *	-0.001	0.270 ^	-0.077	-0.114 ^	0.023
	(0.064)	(0.101)	(0.162)	(0.066)	(0.064)	(0.053)
Prop. GPs older than 60 years, lagged	-0.003	0.063	0.015	-0.064 ^	-0.134 **	0.155 **
	(0.040)	(0.069)	(0.086)	(0.035)	(0.048)	(0.037)
Prop. foreign trained GPs, lagged	0.131	-0.117	0.275 ^	0.097	0.069	0.011
	(0.080)	(0.085)	(0.154)	(0.066)	(0.069)	(0.056)
Constant	1.335 **	0.571 **	0.476 **	0.203 **	0.374 **	0.206 **
	(0.039)	(0.059)	(0.085)	(0.031)	(0.051)	(0.034)
N	8,101	8,291	8,291	8,291	8,291	8,291
Adj. R2	0.046	0.019	0.020	0.034	0.023	0.018

Note: Figures in parentheses are robust standard errors.
Stock of GPs is in natural logarithmic scale, all entries and exits are expressed in untransformed counts.
Included as covariates but not shown in table are year dummies.
Significance levels: ^: 10% *: 5% **: 1%

4. *Districts of workforce shortage*

Ideally in enumerating entries and exits we should exclude IMGs who are restricted in their location choice to Districts of Workforce Shortage (DWS) during their initial years of practice in Australia. Though these doctors are eligible for rural incentive payments, their decision to enter and stay in GPRIP eligible locations are less likely to be affected by the financial incentive than Australian doctors. AMPCo data contain information on qualifications which allows us to identify foreign trained doctors (FTDs), i.e., whether a doctor obtains his or her qualification overseas. But it cannot reliably identify IMGs because a sizeable number of them obtain their qualifications from Australian universities as international students, while some Australian doctors obtain their qualifications overseas. A further issue is, even if we assume that all FTDs are IMGs, we have no information on what proportion of FTDs is under restriction to work in DWS and what proportion has already fulfilled their visa restrictions and is thus no longer restricted in their location choice.

We take the approach of isolating locations designated as DWS in the estimation. We argue that entries into and exits from locations ever designated as DWS are affected by different incentives from non-DWS locations. In the main paper we allow for DWS by including a dummy variable for locations designated as DWS as a covariate. Here we exclude locations that were ever designated as DWS during our sample period, on the basis that these locations attract IMGs who are motivated by different types of incentives. The exclusion removed 3,979 observations from the sample. The OLS and fixed effects estimation results are shown in **Tables C6** and **C7**.

Table C6: OLS estimation of stock of GPs and types of entries and exits, excluding DWS locations

	Dependent variable					
Variable	Stock of GPs	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)						
Newly eligible	-0.122 *	-0.209 **	0.002	0.029	0.112 **	0.008
	(0.051)	(0.052)	(0.057)	(0.021)	(0.035)	(0.031)
Always eligible	-0.002	-0.168 **	-0.046	0.041 *	0.153 **	0.041
	(0.054)	(0.048)	(0.052)	(0.021)	(0.034)	(0.031)
Newly elig. × post-2010	-0.034	0.108 ^	0.035	0.055 *	-0.054	0.031
	(0.061)	(0.062)	(0.069)	(0.028)	(0.043)	(0.037)
Always elig. × post-2010	-0.036	0.033	0.117 *	0.053 *	-0.048	-0.019
	(0.062)	(0.050)	(0.059)	(0.027)	(0.039)	(0.035)
ln(population)	0.242 **	0.182 **	0.177 **	0.06 **	0.100 **	0.059 **
	(0.011)	(0.012)	(0.013)	(0.005)	(0.008)	(0.007)
Prop. pop. older than 65 years	0.379 *	-0.309	-0.539 **	-0.287 **	-0.589 **	0.043
	(0.179)	(0.226)	(0.210)	(0.080)	(0.125)	(0.118)
SEIFA (per cent)	0.342 **	0.442 **	0.255 **	0.034 ^	0.004	0.199 **
	(0.048)	(0.055)	(0.052)	(0.021)	(0.030)	(0.028)
Prop. female GPs, lagged	0.341 **	0.097 **	0.168 **	0.050 **	0.001	0.094 **
	(0.042)	(0.028)	(0.025)	(0.010)	(0.015)	(0.014)
Prop. GPs older than 65 years, lagged	-0.341 **	-0.102 **	-0.101 **	-0.051 **	-0.021	0.063 **
	(0.035)	(0.028)	(0.023)	(0.009)	(0.015)	(0.013)
Prop. foreign trained GPs, lagged	0.017	0.031	0.087 **	0.006	0.110 **	-0.068 **
	(0.0330)	(0.028)	(0.025)	(0.010)	(0.016)	(0.013)
Constant	-1.049 **	-1.200 **	-1.071 **	-0.394 **	-0.637 **	-0.363 **
	(0.123)	(0.135)	(0.143)	(0.054)	(0.082)	(0.074)
N	13,263	13,822	13,822	13,822	13,822	13,822
Adj. R2	0.061	0.035	0.026	0.031	0.027	0.022

Note: Figures in parentheses are robust standard errors.
Included as covariates but not shown in table are year dummies.
Significance levels: ^: 10% *: 5% **: 1%

After excluding DWS locations from the estimation, OLS and fixed effects produce broadly similar estimates to those previously obtained. The effect on new GP entries into newly eligible locations remain positive and statistically significant at 5% level, although smaller in magnitude than the corresponding estimate reported in the main text. The effect of the policy change also appears to be stronger for relocation entries and weaker for other entries and relocation exits, possibly a reflection that fewer relocation entries occur in DWS locations while relocation exits are more common in these locations. Thus excluding DWS locations tend to make the result stronger for relocation entries and weaker for relocation exits. It is interesting to note that, compared to earlier results, the negative effect on other entries is no longer statistically significant. This possibly reflects the fact that DWS locations were designated as DWS in part because they are unattractive to local GPs. Although other entries include GPs moving from overseas, it also includes local GPs resuming practice after a period of absence. We have no information on the relative size of each group. Thus it is plausible that, after excluding DWS locations, the negative effect of GPRIP on newly eligible locations becomes weaker than before.

Table C7: Fixed effects estimation of stock of GPs and types of entries and exits, excluding DWS locations

	Dependent variable					
Variable	Stock of GPs	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)						
Newly elig. × post-2010	0.016	0.118 *	0.084	0.066 *	-0.055	0.037
	(0.021)	(0.056)	(0.067)	(0.029)	(0.040)	(0.033)
Always elig. × post-2010	-0.003	0.035	0.140 **	0.060 ^	-0.058	0.013
	(0.023)	(0.052)	(0.053)	(0.032)	(0.042)	(0.033)
Prop. female GPs, lagged	0.164 *	-0.143 ^	0.224 **	-0.058 *	-0.085 *	0.106 **
	(0.040)	(0.080)	(0.072)	(0.025)	(0.040)	(0.037)
Prop. GPs older than 60 years, lagged	0.031	0.142 *	-0.049	-0.018	-0.084 **	0.198 **
	(0.028)	(0.066)	(0.055)	(0.020)	(0.031)	(0.028)
Prop. foreign trained GPs, lagged	-0.037	0.003	0.122	-0.068 **	-0.036	-0.102 *
	(0.043)	(0.101)	(0.087)	(0.026)	(0.045)	(0.040)
Constant	1.497 **	0.764 **	0.615 **	0.224 **	0.366 **	0.286 **
	(0.022)	(0.046)	(0.053)	(0.016)	(0.026)	(0.023)
N	13,263	13,822	13,822	13,822	13,822	13,822
Adj. R2	0.034	0.014	0.011	0.025	0.018	0.020

Note: Figures in parentheses are robust standard errors.
Included as covariates but not shown in table are year dummies.
Significance levels: ^: 10% *: 5% **: 1%

5. *Regressions using average values pre- and post-GPRIP*

A concern about the AMPCo data we rely on for tracking the movement of doctors is that its accuracy relies largely on timely updating by doctors of changes in their practice location. However, changing practice can be a major disruption and updating practice location with AMPCo may not be high on the priority list of GPs who move. Hence changes in practice locations may be reported with a time lag in some cases. We therefore compute average values of the stock of GPs, and entries and exits by each location, over the pre- and post-GPRIP periods. We hope that averaging over time will smooth out year-to-year fluctuations due to misreporting. We then implement difference-in-difference regressions using these average values as the dependent variable. The independent variables are likewise averaged over time pre- and post-GPRIP for each location. Consequently each location is now observed twice, once before and once after GPRIP. Note that the independent variables describing population characteristics are time invariant throughout the study period and hence no averaging is needed.

The results are shown in **Tables C8** and **C9**. OLS and fixed effects estimates are broadly similar to the previous results. The effect on new GP entries into newly eligible locations remain positive and statistically significant with similar magnitude as before. Likewise, the effect of the policy change also appears similar for relocation entries, other entries and relocation exits.

Table C8: OLS estimation of stock of GPs, and types of entries and exits, average values pre- and post GPRIP

	Dependent variable					
Variable	Stock of GPs	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)						
Newly eligible	-0.294 **	-0.126 *	-0.038	0.010	0.108 **	-0.022
	(0.061)	(0.051)	(0.051)	(0.017)	(0.032)	(0.027)
Always eligible	-0.125 ^	-0.164 **	-0.069	0.045 *	0.150 **	0.018
	(0.073)	(0.047)	(0.051)	(0.018)	(0.036)	(0.026)
Newly elig. × post-2010	0.023	0.030	-0.004	0.058 **	-0.062 *	0.031
	(0.042)	(0.042)	(0.043)	(0.018)	(0.027)	(0.023)
Always elig. × post-2010	-0.014	0.066 *	0.063 *	0.007	-0.052 *	0.007
	(0.031)	(0.028)	(0.030)	(0.013)	(0.022)	(0.018)
Post 2010	0.020	-0.078 **	-0.103 **	0.013 ^	0.034 **	-0.027 *
	(0.018)	(0.021)	(0.021)	(0.008)	(0.012)	(0.011)
ln(population)	0.258 **	0.145 **	0.151 **	0.050 **	0.098 **	0.052 **
	(0.020)	(0.013)	(0.014)	(0.005)	(0.010)	(0.007)
Prop. pop. older than 65 years	1.251 **	-0.304	-0.338	-0.090	-0.477 **	0.036
	(0.318)	(0.279)	(0.245)	(0.075)	(0.145)	(0.137)
SEIFA (per cent)	0.144	0.341 **	0.148 *	-0.006	-0.017	0.161 **
	(0.102)	(0.080)	(0.075)	(0.024)	(0.039)	(0.038)
District of Workforce Shortage (DWS)	-0.239 **	-0.082 **	-0.036	-0.029 *	0.013	-0.037 ^
	(0.059)	(0.031)	(0.038)	(0.014)	(0.027)	(0.019)
Prop. female GPs, averaged	0.149 *	0.103 **	0.089 **	0.045 **	0.039 *	0.055 **
	(0.064)	(0.030)	(0.030)	(0.010)	(0.017)	(0.015)
Prop. GPs older than 65 years, averaged	-0.273 **	-0.150 **	-0.054 ^	-0.040 **	0.037 *	0.027 ^
	(0.058)	(0.029)	(0.029)	(0.009)	(0.018)	(0.015)
Prop. foreign trained GPs, averaged	0.023	0.048	0.060 *	0.013	0.098 **	-0.048 **
	(0.0520)	(0.029)	(0.028)	(0.009)	(0.018)	(0.014)
Constant	-1.338 **	-0.799 **	-0.813 **	-0.339 **	-0.682 **	-0.318 **
	(0.221)	(0.153)	(0.163)	(0.052)	(0.10)	(0.085)
N	6,505	6,505	6,505	6,505	6,505	6,505
Adj. R2	0.108	0.076	0.051	0.036	0.040	0.029

Note: Figures in parentheses are robust standard errors.

Significance levels: ^: 10% *: 5% **: 1%

Table C9: Fixed effects estimation of stock of GPs, and types of entries and exits, average values pre- and post GPRIP

	Dependent variable					
Variable	Stock of GPs	Relocation entries	Relocation exits	New entries	Other entries	Other exits
Eligibility (Ref: Never eligible)						
Newly elig. × post-2010	0.027	0.004	0.054	0.075 **	-0.069 *	0.041 ^
	(0.023)	(0.044)	(0.046)	(0.020)	(0.029)	(0.024)
Always elig. × post-2010	-0.019	0.079 **	0.074 *	0.009	-0.048 *	0.023
	(0.018)	(0.028)	(0.030)	(0.014)	(0.024)	(0.018)
Post 2010	0.051 **	-0.117 **	-0.059 **	0.016 ^	0.028 *	-0.005
	(0.010)	(0.022)	(0.022)	(0.009)	(0.013)	(0.012)
District of Workforce Shortage (DWS)	-0.057	0.012	0.078	-0.015	-0.067	-0.045
	(0.049)	(0.061)	(0.091)	(0.040)	(0.060)	(0.052)
Prop. female GPs, averaged	0.042	0.017	-0.020	0.052 *	0.070 *	0.024
	(0.064)	(0.059)	(0.066)	(0.022)	(0.034)	(0.036)
Prop. GPs older than 60 years, averaged	0.032	0.046	0.042	-0.015	0.162 **	0.030
	(0.048)	(0.046)	(0.047)	(0.018)	(0.031)	(0.026)
Prop. foreign trained GPs, averaged	-0.020	-0.063	0.052	-0.032	0.090 *	-0.035
	(0.070)	(0.063)	(0.068)	(0.023)	(0.039)	(0.037)
Constant	1.181 **	0.652 **	0.570 **	0.131 **	0.193 **	0.253 **
	(0.038)	(0.037)	(0.039)	(0.015)	(0.025)	(0.022)
N	6,505	6,505	6,505	6,505	6,505	6,505
Adj. R2	0.018	0.014	0.002	0.014	0.010	0.001

Note: Figures in parentheses are robust standard errors.
Significance levels: ^: 10% *: 5% **: 1%